Faculty of Technology

Proposal for Approval – submitted to Mumbai University

Outline of Research proposal submitted for the Doctor of Philosophy (Tech) Degree in Mechanical Engineering

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11	**Table of content**	

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This is to certify that the PhD topic approval presentation by "**Mr. Mukund Padmakar Kavekar**" on "**Development of Intelligent System for Machine Diagnosis using Artificial Intelligence**" has been approved and the report for the same is being submitted herewith.

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Abstract:

Sensor technology has exponentially increased the amount of data extracted from production processes. Artificial intelligence (AI) refers to simulation of human intelligence in machines and computers to mimic the problem-solving and decision-making capabilities of the human mind. Machine Learning (ML) is a technique of Artificial Intelligence (AI) and Data Analysis that help to construct analytical model. Machine Learning and Artificial Intelligence (AI & ML) is based on the study of computer algorithms that can update automatically through pattern recognition, technical experience, and data analysis. Decision making through AI incorporated mechanism or system take minimum time with less human intervention. ML algorithms are not explicitly programmed, instead of that it gets trained through a sample data which is known as training data. Algorithm training in ML algorithms is used in a wide variety of applications, like biotechnology, biomaterial, e-mail filtering, speech recognition, prediction, and robotics. [1]

A key aspect of Industry 4.0 is automation, digital interconnectivity, and a high degree of flexibility that allows all systems involved to self-reconfigure independently. [2] AI & ML has a significant role in Industry 4.0 In Mechanical Engineering AI algorithms can upgrade manufacturing space, streamline supply chain management, predict failure of machine components, automated driving, etc.

Machine maintenance keeps the mechanical facility in working order by periodic servicing, repairing, and replacing worn out/nonfunctioning parts. It is classified as a) Breakdown maintenance b) Preventive maintenance, c) Predictive maintenance and d) Proactive maintenance. Machine maintenance is a crucial activity, which affects the productivity of the entire manufacturing plant.

Research and implementation of AI & ML techniques in specific areas like medical diagnosis, computer vision, traffic prediction, etc. have been explored in substantial amounts with real time databases. Comparatively use of AI and ML in the mechanical field and availability of real time data is less, so more avenues are there for real time data acquisition of mechanical systems using appropriate sensors and use of AI & ML for mechanical applications like Machinery fault diagnostics and machine health monitoring. Proposed Work is focused on the development of an intelligent system for machine diagnosis using Artificial Intelligence.

Keywords: Predictive maintenance (PdM), Artificial Intelligence (AI), Machine learning (ML),

prediction of data, and flexible adaption of AI system". It is also useful to detect patterns based on available data for a deep understanding of the problem for decision making [3].

1.2 Machine Learning (ML): It is a branch of Artificial Intelligence (AI) and Computer Science which focuses on data analysis. ML algorithms are used to replicate the way humans learn, gradually improving its accuracy. ML is a part of AI which allows a machine to automatically learn from historical data without being explicitly programmed. [3]

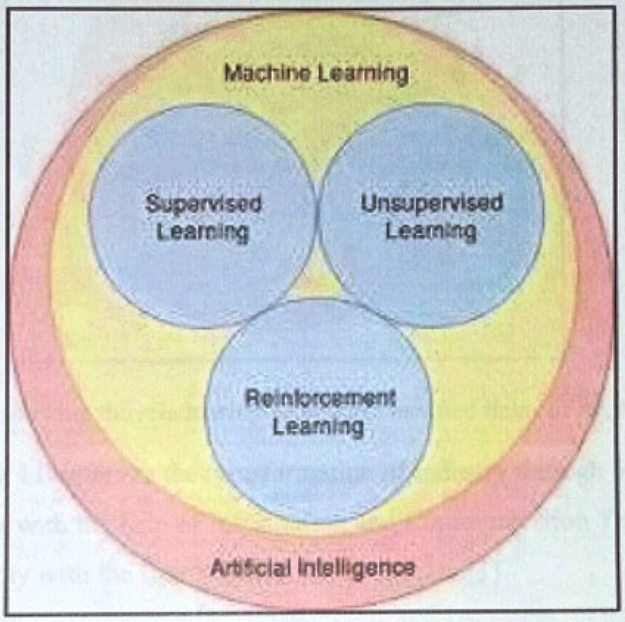

Fig.2. Venn diagram of AI Circle [1]

ML classified into three categories:

a) **Supervised Machine Learning:** In learning algorithms are fed by a set of labelled training data. Few important algorithms in this are Support Vector Machines, Naïve Bayes, Nearest Neighbor, Random Forest, XG Boost, etc.

b) **Unsupervised Machine Learning:** In learning algorithm algorithms are fed an unlabelled training dataset.to identify patterns in data sets containing data points that are neither classified nor labeled. Few important algorithms are K Means, K Medoids, Gaussian Mixture, Hidden Marko Model, Neural Network, etc.

c) **Reinforcement Machine Learning:** In this learning training method based on rewarding desired behaviors and/or punishing undesired ones. In general, a reinforcement learning agent is able to perceive and interpret its environment, take actions and learn through trial and error.

1.3 Data Science: It is the domain of study that deals with vast volumes of data using modern tools and techniques to find unseen patterns, derive meaningful information, and make business decisions.

A data scientist uses tools such as statistical modeling, visualization methods, hypothesis testing, and ML algorithms (AI uses ML as well). [4]

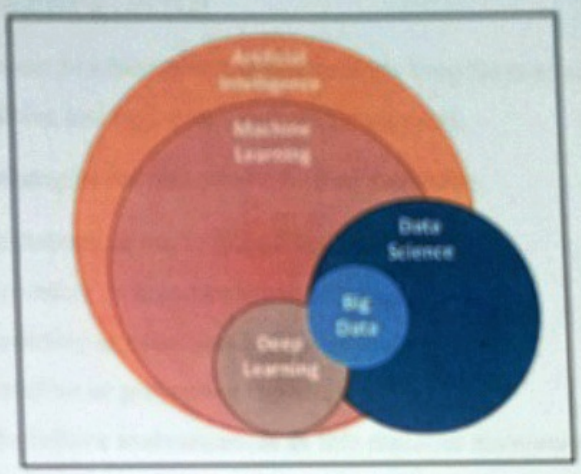

Fig.3. Venn diagram showing the relationship between diversified fields of AI, ML and DS [17]

1.4 Industry 4.0: Industry 4.0 refers to the transformation of industry through intelligent networking of machines and processes with the help of Information and Communication Technology (ICT). The term is used interchangeably with the fourth industrial revolution. [1]

1.4.1 Industry 4.0 Technologies: Various technologies used in Industry 4.0 as below

i. The internet of things (IoT)
ii. The industrial internet of things (IIoT)
iii. Cyber-physical systems (CPS)
iv. Smart manufacture.
v. Smart factories.
vi. Cloud computing.
vii. Cognitive computing.
viii. Artificial intelligence

1.5 Application of AI & ML in Mechanical Engineering

a) Predictive maintenance
b) Fault diagnosis
c) Quality inspection

d) Improving the safety of working places
e) Product development and manufacturing
f) Supply Chain Management
g) Products upgrading
h) Self-driving cars [12]

1.6 Machine Maintenance: Machine maintenance refers to keep the machines in a facility in working order by servicing, repairing and replacing nonfunctioning parts.

Machine maintenance strategies are classified into four categories.

i. Breakdown or run to failure maintenance
ii. Preventive or time-based maintenance
iii. Predictive or condition-based maintenance
iv. Proactive or prevention maintenance.

i. Breakdown or run to failure maintenance: In this machine maintenance strategy, the machinery is allowed to run till its component failure and the repairing or replacement of damaged components is carried out just before or after its failure. This strategy is applicable where breakdown does not hamper much on productivity. Major disadvantage of the strategy is that the maintenance department may face unplanned maintenance operation. Also, it requires large inventory and spare parts or preplanning to assure immediate availability of the required inventory to respond immediately. [4]

ii. Preventive or time-based maintenance: In this maintenance strategy periodic maintenance activity is carried out after specific time intervals or runtime usage of machine. In this method the repairing or replacement of defective components is carried out before failure. This is a comparatively better strategy for equipment that do not run continuously, and where the machine operator or supervisor have enough skill to perform the preventive maintenance work.

The main shortcoming of this method is the performance of maintenance tasks too early or too late. Equipment is taken out for overhaul after a certain number of running hours. It may happen that parts get replaced before functional failure; Remaining Useful Life (RUL) may waste in this method. [4]

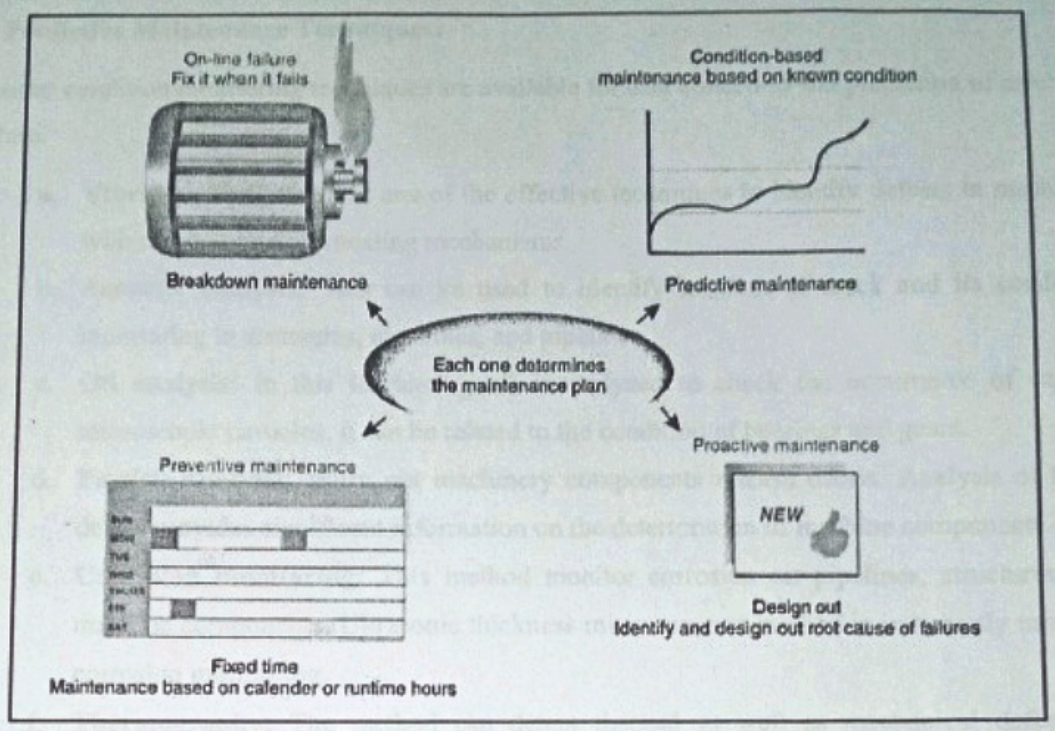

Fig.4. Maintenance Philosophies [4]

iii. Predictive or condition-based maintenance: In this strategy maintenance activity is carried out only after or just before the failure of machine components. Critical components and machines are condition monitored and when unhealthy pattern is detected, the defective parts in the machine are identified and replaced or repaired. Significant advantage of this method is optimum utilization of Remaining Useful Life (RUL) of machine and its component. Few shortcomings in the strategy are (i) an incorrect assessment of the deterioration of machines increase maintenance work. (ii) special equipment, sensors, microcontroller etc. required for condition monitoring. (iii) expert and trained professional for data acquisition and analysis to take appropriate decision. [4]

iv. Proactive or prevention maintenance: This philosophy lays primary emphasis on tracing all failures to their root cause. Each failure is analyzed, and proactive measures are taken to ensure that they are not repeated. It utilizes all of the predictive/preventive maintenance techniques in conjunction with Root Cause Failure Analysis (RCFA). RCFA detects and pinpoints the problems that cause effects. It ensures that appropriate installation and repair techniques are adopted and implemented. It may also highlight the need for redesign or modification of equipment to avoid recurrence of such problems. [4]

1.7. Predictive Maintenance Techniques:

Various condition monitoring techniques are available for data collection and prediction of machine failure:

a. **Vibration analysis:** It is one of the effective techniques to identify defects in machines with rotating or reciprocating mechanisms.
b. **Acoustic analysis:** This can be used to identify location of crack and its condition monitoring in structures, machines, and pipelines.
c. **Oil analysis:** In this lubricating oil is analyzed to check the occurrence of certain microscopic particles. it can be related to the condition of bearings and gears.
d. **Particle analysis:** Worn out machinery components release debris. Analysis of these debris provides significant information on the deterioration of machine components.
e. **Corrosion monitoring:** This method monitor corrosion on pipelines, structures and machine components, Ultrasonic thickness measurements method is commonly used for corrosion monitoring.
f. **Thermography:** The method can detect thermal as well as mechanical defects in electromechanical instruments like boiler, generators, furnaces, etc. It used to detect cell damage in carbon fiber structures of aircrafts.
g. **Performance monitoring:** Periodic performance evaluation is one of the effective techniques to determine the operational problems in machineries. [4]

1.8 Artificial Intelligence and Machine Learning for Predicative Maintenance

PdM deals with fault prediction before its occurrence. Condition monitoring based maintenance approach employs diagnostic and prognostic method.

Condition monitoring approach is classified into three categories: Statistical approach, Model-based approach, and AI approach. Statistical approach requires good mathematical skill, Model-based approach requires mechanical knowledge, while AI approach requires data acquisition system and skilled professionals for data analysis. [4]

AI & ML based PdM strategy has been increasingly applied in past few years. It is a powerful tool for developing intelligent algorithms for various applications. Few important algorithms are Support Vector Machines, Naïve Bayes, Nearest Neighbor, Random Forest, XG Boost, etc. ML approach is capable to handle high dimensional and multivariate data and identify relationships between variables within the available data. [5]

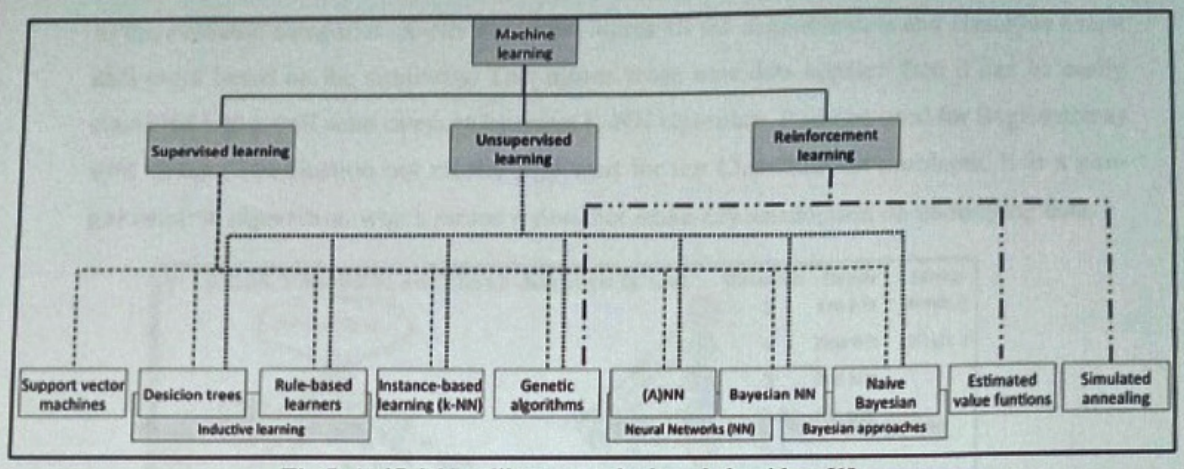

Fig.5. Artificial Intelligence methods and algorithm. [1]

1.9 AI & ML techniques for Mechanical Maintenance: AI & ML algorithms used for PdM are listed below:

i. K-Nearest Neighbor
ii. Logistic Regression
iii. Naïve Bayes

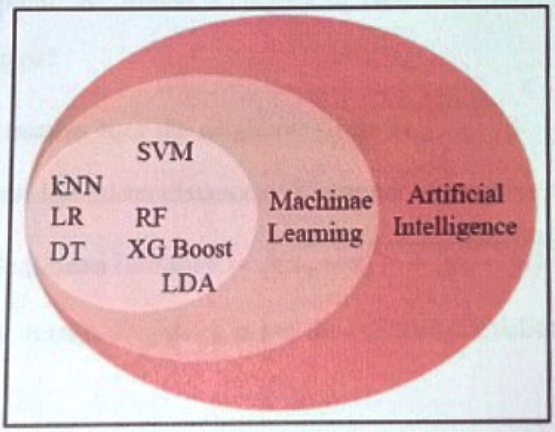

Fig.6. Venn diagram showing the Various AI and ML techniques for PdM [12]

iv. Support Vector Machines
v. Decision Tree
vi. XGBoost
vii. Random Forest

1.9.1 K-Nearest Neighbor:

K-NN algorithm is supervised learning algorithm which assumes the similarity between input data and trained categorized database and put the new case into the category that is most similar

to the available categories. K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K-NN algorithm. It can be used for Regression as well as for Classification but mostly it is used for the Classification problems. It is a **non-parametric algorithm**, which means it does not make any assumption on underlying data.

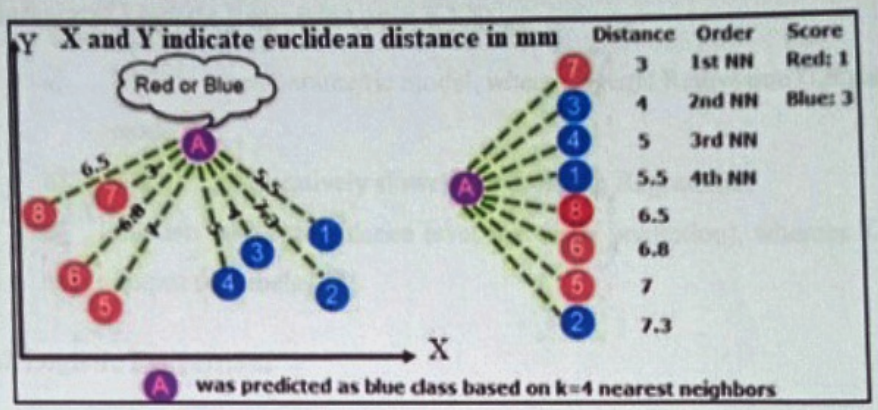

Fig.7. K-Nearest neighbor [12]

Working of K-Nearest Neighbor: Suppose training data categorized in two categories, i.e., red and blue, new data point 'A' Added. Category of New data point find out by KNN. Algorithm by following steps:

Step-1: Select the number K of the neighbors (Here 8)

Step-2: Calculate the Euclidean distance of K number of neighbors

$$\text{Euclidean Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Step-3: Take the K nearest neighbors as per the calculated Euclidean distance. (Here K=4)

Step-4: Among these K neighbors, count the number of the data points in each category. (Blue=3, Red=1)

Step-5: Assign the new data points to that category for which the number of the neighbor is maximum. (A is assigned to Blue as number of neighbors are more) [18].

Advantages:

i. Simple machine learning model.

ii. Two hyperparameters (K Value, Distance Function) to tune.

Disadvantages:

i. Selection of K-Value require expert and experience professional.
ii. Its computation cost is high but comparatively less accuracy.
iii. Proper scaling should be provided for fair treatment among features.

Advantages of Logistic Regression over KNN:

a) KNN is a non-parametric model, where Logistic Regression (LR) is a parametric model.
b) KNN is comparatively slower than Logistic Regression.
c) LR can derive confidence level (about its prediction), whereas KNN can only output the labels [62].

1.9.2 Logistic Regression:

Logistic Regression is supervised learning algorithm that can be used for It is used for predicting the categorical dependent variable using a given set of independent variables. It is based on the concept of ensemble learning, in this process multiple classifiers combined to solve a complex problem and performance improvement of model. It gives the probabilistic values which lie between 0 and 1. Logistic Regression is a significant ML algorithm because it has the ability to provide probabilities and classify new data using continuous and discrete datasets. Accuracy of prediction get increased with increase in number of trees. The value of the logistic regression must be between 0 and 1, which cannot go beyond this limit, so it forms a curve like the "S" form. The S-form curve is called the Sigmoid function or the logistic function.

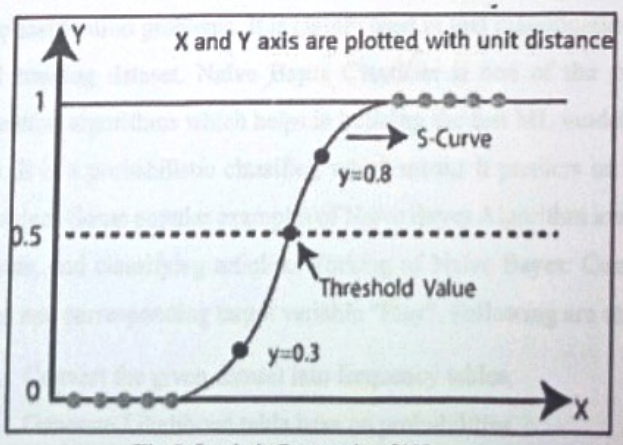

Fig.8. Logistic Regression [12]

Assumptions for Logistic Regression:

1. The dependent variable must be categorical in nature.
2. The independent variable should not have multi-collinearity.

Advantages:

i. Easy, fast, and simple classification method.
ii. θ parameters explains the direction and intensity of significance of independent variables over the dependent variable.
iii. It can be used for multiclass classifications.
iv. Loss function is always convex.

Disadvantages:

i. It cannot be applied on non-linear classification problems.
ii. Proper selection of features is required.
iii. Good signal to noise ratio is expected.
iv. Collinearity and outliers tamper the accuracy of LR model.

Advantages of Naïve Bayes over Logistic Regression

a) LR is a discriminative model while Naïve bayes is a generative model.
b) LR+ Regularization works well with small datasets, whereas Naïve bayes can achieve similar performance. [62].

1.9.3 Naïve Bayes:

Naïve Bayes algorithm is a supervised learning algorithm, It is based on Bayes theorem and used for solving classification problems. It is mainly used in text classification that includes a high-dimensional training dataset. Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast ML models that can make quick predictions. It is a probabilistic classifier, which means it predicts on the basis of the probability of an object. Some popular examples of Naïve Bayes Algorithm are spam filtration, Sentimental analysis, and classifying articles. Working of Naïve Bayes: Consider dataset of weather conditions and corresponding target variable "Play". Following are steps:

1. Convert the given dataset into frequency tables.
2. Generate Likelihood table base on probabilities.

Use Bayes theorem to calculate the posterior probability

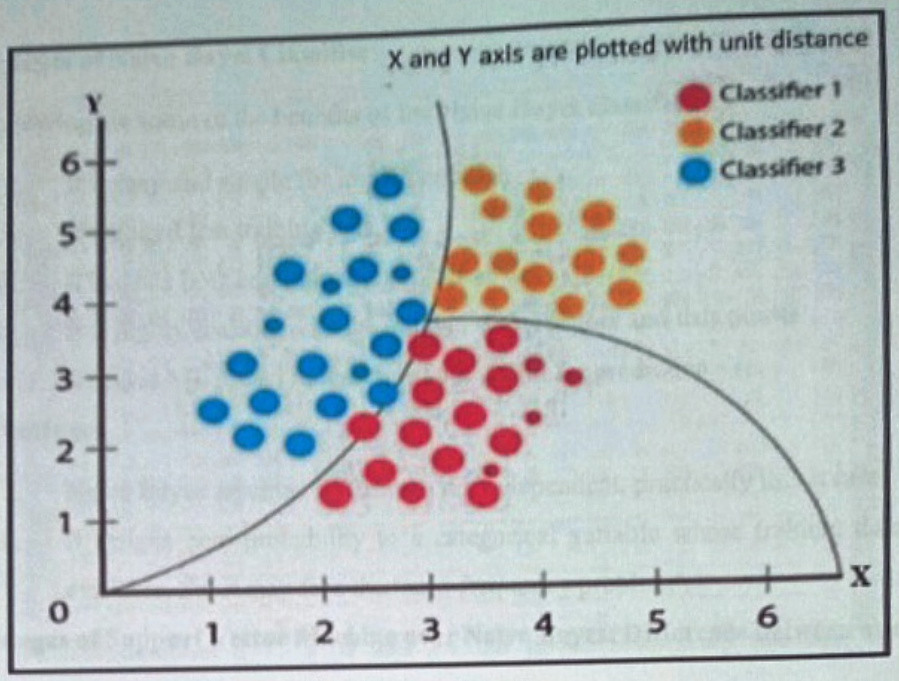

Fig.9. Naïve Bayes [12]

Table1: Naïve Bayes [12]

Weather	Play (Yes)	Play (No)	
Overcast	5	0	5/14=0.35
Rainy	2	2	4/14=0.29
Sunny	3	2	5/14=0.35
Total	10	4	
	10/14=0.71	4/14=0.29	

P (Yes | Sunny) = P (Sunny | Yes) *P(Yes)/P(Sunny)

P (Sunny | Yes) = 3/10= 0.3, P(Sunny)= **0.35**

P(Yes)=0.71, So P (Yes | Sunny) = 0.3*0.71/0.35= **0.60**

P (No | Sunny) = P (Sunny | No) *P(No)/P(Sunny)

P (Sunny | NO) = 2/4=0.5, P(No)=0.29 P(Sunny)=0. **0.35**

P (No | Sunny) = 0.5*0.29/0.35 = 0.41,

P (Yes | Sunny)>P (No | Sunny)

Hence on a Sunny day, Player can play the game.

Advantages of Naïve Bayes Classifier

The following are some of the benefits of the Naive Bayes classifier:

i. It is easy and simple for implementation.
ii. It required less training data.
iii. It handles both continuous and discrete data
iv. It is highly scalable with the number of predictors and data points
v. It makes ML model in less time so it useful for prediction.

Disadvantages

i. Naive Bayes assumes all features are independent, practically this is rare.
ii. It assigns zero probability to a categorical variable whose training dataset not available. So, it may face the 'zero-frequency problem'.

Advantages of Support Vector Machine over Naïve Bayes: Difference between and Naïve Bayes

a) SVM is more powerful to address non-linear classification tasks.
b) SVM is good in multivariate data. high dimensional spaces required for classification.
c) SVM is a binary model in its conception, so it could be applied to classifying multiple classes with very good results [64].

1.9.4 Support Vector Machine

Support Vector Machine algorithm is supervised learning algorithm that can be used for both classification and regression problems, but mostly it is preferred for solving Classification problems. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so new data point can allocate in the correct category. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine [64].

Working of Support Vector Machine

Consider the below diagram in which there are two different categories (Class1 and Class 2) that are classified using a decision boundary.

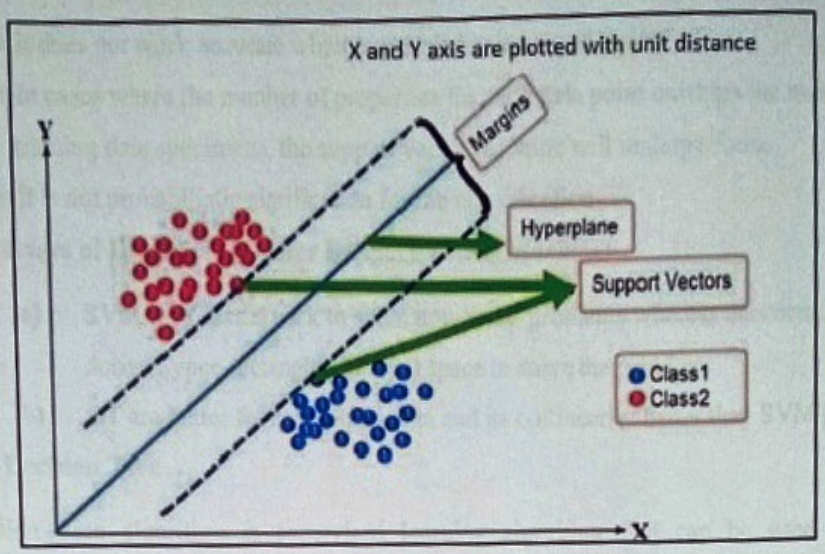

Fig.10. Support Vector Machine [12]

Steps of Support Vector Machine

a) Data Pre-processing step
b) Fitting the SVM classifier to the training set
c) Predicting the test set result
d) Creating the confusion matrix
e) Visualizing the training set result

Suppose input is a hatchback car that also has some features SUV, to identify whether it is hatchback or SUV, Model can be created by using the SVM algorithm. Training of model will do with lots of images of hatchback and SUV cars so that it can learn about its various feature and then testing done for input data. So as support vector creates a decision boundary between these two data and choose extreme cases (support vectors), it will see the extreme case of hatchback and SUV cars. On the basis of the SVM, it will classify it as a hatchback car.

Advantages of support vector machine:

i. Support vector machine works efficiently when there is margin of dissociation between classes.
ii. It is more productive in high dimensional spaces.
iii. It is effective in instances where the number of dimensions is larger than the number of specimens.
iv. Support vector machine is comparably memory systematic.

Disadvantages of support vector machine:

i. Support vector machine algorithm is not a suitable for large data sets.

ii. It does not work accurate when target classes are overlapping.

iii. In cases where the number of properties for each data point outstrips the number of training data specimens, the support vector machine will underperform.

iv. It is not probabilistic clarification for the classification

Advantages of Decision Tree over Support Vector Machine:

a) SVM uses kernel trick to solve non-linear problems whereas decision trees (DT) derive hyper-rectangles in input space to solve the problem.

b) DT are better for categorical data and its collinearity better than SVM [64].

1.9.5 Decision Tree

Decision Tree algorithm is supervised learning algorithm that can be used for both classification and regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules, and each leaf node represents the outcome. Decision Trees usually mimic human thinking ability while deciding, so it is easy to understand. In a decision tree, for predicting the class of the given dataset, the algorithm starts from the root node of the tree. This algorithm compares the values of root attribute with the record (real dataset) attribute. Based on the comparison, follows the branch, and jumps to the next node.

Working of Decision Tree: Decision tree for Proposal on starting of Welding electrode manufacturing Plant.

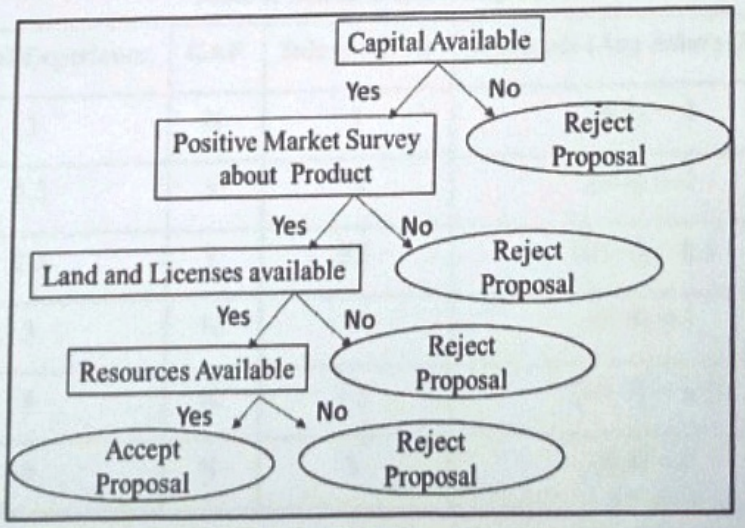

Fig.11. Decision Tree

Advantages:

i. Data does not required Pre-processing.
ii. Distribution of data does not require assumption.
iii. Capable to handle collinearity efficiently.
iv. Decision trees suitable for prediction.

Disadvantages:

i. Overfitting tendency of ML model. Decision tree can be used to solve this issue.
ii. Prone to outliers.
iii. Tree may grow to be very complex while training complicated datasets.
iv. Data loss while handling continuous variables.

Advantages of XGBoost over Decision Tree

a) XGBoost is similar to Decision tree, Significant difference is it consider gradient or weightage for more accuracy.
b) The algorithm performs better with more leaves and gradient in the decision tree.

1.9.6 XGBoost

XGBoost is an implementation of Gradient Boosted decision trees. In this algorithm, decision trees are created in sequential form. Weights play an important role in XGBoost. Weights are assigned to all the independent variables which are then fed into the decision tree which predicts results [65].

Table 2. Data for XGBoost Algorithm

Years of Experience	GAP	Salary (LPA)	Residuals (Avg Salary-Salary)
1	N	4	(4-6) = -2
1.5	Y	4	(4-6) = -2
2.5	Y	5.5	(5.5 -6) = 0.5
3	N	7	(7 -6) = 1
5	N	7.5	(7.5 -6) = 1.5
6	N	8	(8-6) = 2

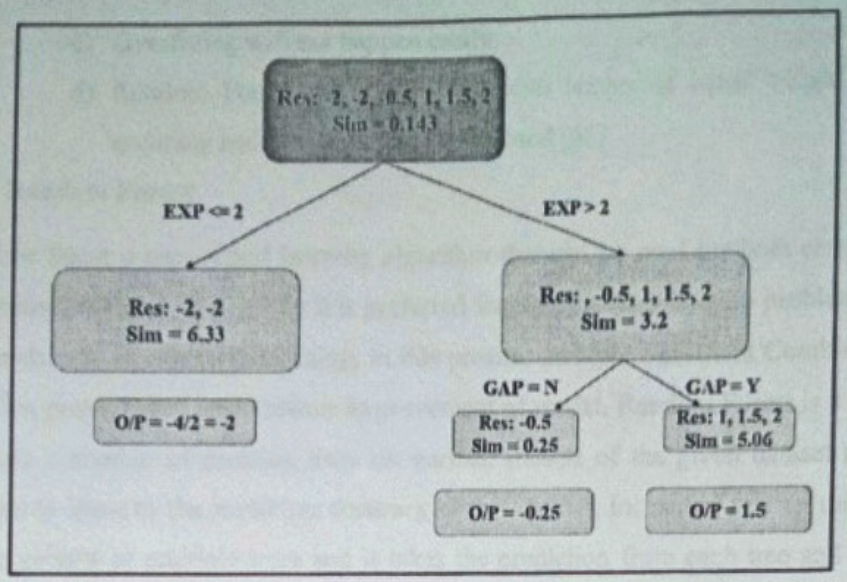

Fig.12. XG Boost [12]

Similarly, the algorithm produces more than one decision tree and combine them additively to generate better estimates.

Advantages:

i. It is Highly Flexible.
ii. It uses the power of parallel processing.
iii. It is faster than another ML algorithm.
iv. It supports regularization
v. It has an in-built capability to handle missing values.
vi. It's cross-validation at each iteration is possible and thus optimum number of boosting iterations required can get in a single run.

Disadvantages:

i. It does not perform so well on sparse and unstructured data.
ii. It unable to extrapolate target values beyond the availability of training data while predictions.

Advantages of Random Forest over XGBoost

a) In Random Forest, the decision trees are built independently so that if there are five trees in an algorithm, all the trees are built at a time but with different features and data present in the algorithm. In XGBoost only one tree at a time.
b) Multiclass object detection I easy in RF it is easy to tune and works well even if there are lots of missing data and more noise.

c) Overfitting will not happen easily.

d) Random Forest has many trees with leaves of equal weight so that high accuracy and precision can be obtained [65]

1.9.7 Random Forest

Random forest is supervised learning algorithm that can be used for both classification and regression problems, but mostly it is preferred for solving classification problems. It is based on the concept of ensemble learning, in this process multiple classifiers Combined to solve a complex problem and performance improvement of model. Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. Instead of relying on one decision tree, it consist of multiple trees and it takes the prediction from each tree and based on the majority votes of predictions. Based on majority, it predicts the final output. Accuracy of prediction get increased with increase in number of trees [63].

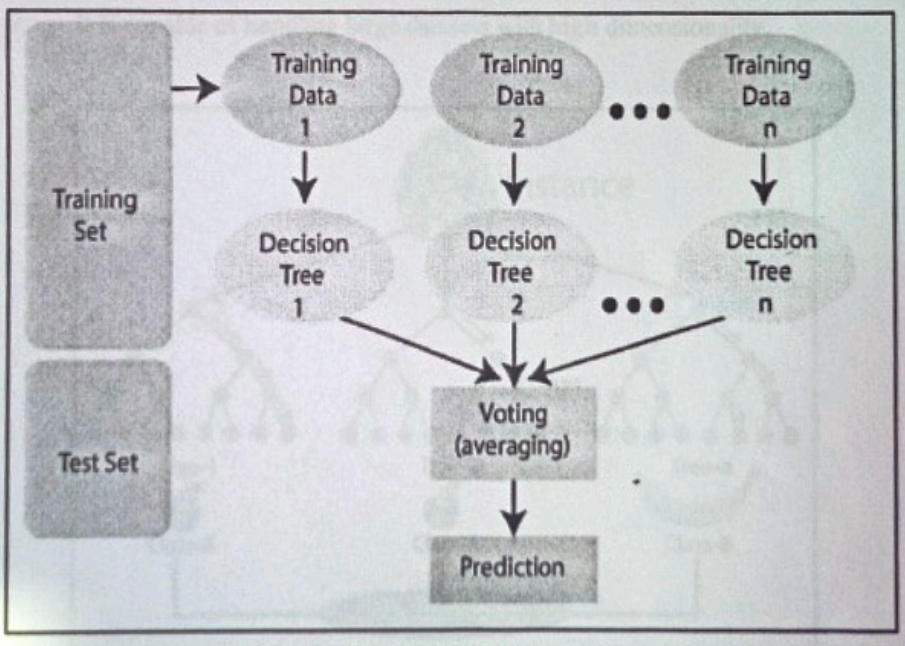

Fig.13. Random Forest [12]

Assumptions in Random Forest:

1. There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.
2. The predictions from each tree must have very low correlations.

Steps in Random Forest

The Working process can be explained in the below steps and diagram:

- **Step-1:** Select random K data points from the training set.
- **Step-2:** Build the decision trees associated with the selected data points (Subsets).
- **Step-3:** Choose the number N for estimated no. of decision trees.
- **Step-4:** Repeat Step 1 & 2.
- **Step-5**: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

Advantages of Random Forest:

i. Random Forest is capable of performing both Classification and Regression tasks.
ii. It takes less training time as compared to other algorithms.
iii. It predicts output with high accuracy, even for the large dataset it runs efficiently.
iv. It can also maintain accuracy when a large proportion of data is missing.
v. It is capable of handling large datasets with high dimensionality.

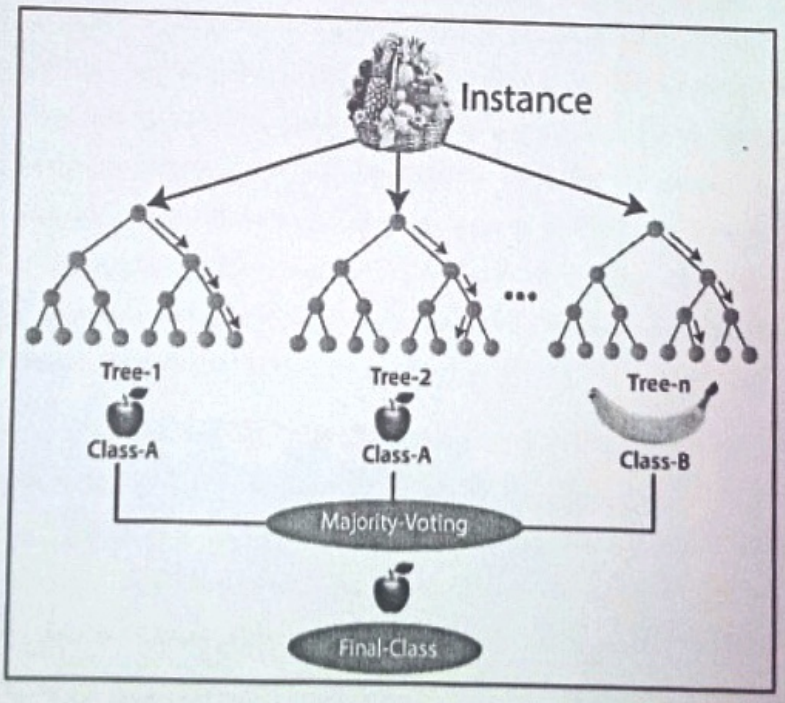

Fig.14. Random Forest Tree [12]

Disadvantages of Random Forest:

i. Although random forest can be used for both classification and regression tasks, it is not more suitable for Regression tasks.

ii. It requires much computational power as well as resources as it builds numerous trees to combine their outputs.

iii. It takes much time for training as it combines a lot of decision trees to determine the class.

Applications of Random Forest:

1. **Banking:** Banking sector mostly uses this algorithm for the identification of loan risk.
2. **Medicine:** With the help of this algorithm, disease trends and risks can be identified.
3. **Land Use:** We can identify the areas of similar land use by this algorithm.
4. **Marketing:** Marketing trends can be identified using this algorithm [63].

Literature Review:

2.1 Literature review on overview of Machine Learning in Mechanical Engineering:

Systematic literature review of the available ML techniques and its comprehensive study with potential benefits are discussed with suitability of ML techniques in manufacturing application. Advantages, shortcomings, challenges and applications of ML in manufacturing were discussed by Thorsten Wuest. et al., 2016. [1] Further the study can be used for practical implementation of ML in manufacturing domain.

In translating the technology to improve the world, ML plays an important role. N.K. Geetha et.al., 2020. focussed on techniques of computer simulation of human behavioral learning. Case studies on adoptability of ML algorithm such as symbolic regression and random forest regression were used to predict the machine component failure. Condition-based maintenance is one of the emerging techniques. Future scope of condition monitoring is not only limited to predictive maintenance, but further research work can also be extended to design intelligent devices to continuously monitor its health using IOT based data acquisition, data analysis and online diagnostic tools. [3]

Rebecca Welte et al., 2020. worked on various challenges in implementation of ML for predictive maintenance in small and medium sized enterprises. They segregated ML implementation in four phases as preparation phase, design phase, implementation phase and Monitoring phase. In the initial phase of the implementation process, AI & ML experts were integrated, and a step-by-step transformation process was followed for a dual skill approach to internal competency development followed by testing and implementation in a medical technology company. In small and medium scale gradual implementation of ML techniques and employee's motivation turn in to irreversible and sustainable technique for strategic growth of a company [5].

Condition monitoring technique and PdM was elaborated in two important parts of the systematic literature survey presented by Sebastian Schwendemann et al., 2021. The initial part presented literature survey on bearing and its types of failure, including bearing health monitoring and identification of unhealthy conditions. Focus was also given to detection of fault location in the bearing (e.g., at the inner/outer ring/rollers/cage of the bearing) and the severity of fault. The second part focused on the survey for prediction of Remaining Useful Life (RUL). A comparative study of various techniques being used in ML for bearing fault diagnostics and prognostics play an essential role in improving system decision-making, reliability of machine and products manufactured by machine. Recent senser technology, data acquisition and big data analytics tools gives popularity to

data-driven prognostic approach [33]. Present work does not approach transfer learning between different bearing types for remaining useful life and only a few for classification, Further study can be extended for Remaining Useful Life (RUL) prediction.

Yuxin Wen et al., 2022. provided the most recent data driven prognostic techniques. It is the essential process for PdM Researcher suggested the methodologies, current challenges, and future scope of machine prognostics boost predictive maintenance, accuracy, reliability and productivity with intelligent decision-making [51].

2.2. Literature review on application of Machine Learning in Mechanical Engineering:

Predictive Maintenance (PdM) is a condition monitoring based machine maintenance strategy (CBM) that monitor health of machine components and maintenance activity carried out as per prediction through data analysis just before the breakdown. Condition monitoring also ensure optimum utilization of Remaining Useful Life (RUL). It also avoids unnecessary preventive maintenance activities. ML (ML) is growing technology of condition monitoring and fault diagnosis. Considerable research is underway for AI & ML based PdM.

Sujie Genga et.al., 2022 PdM method was proposed in this paper by combining the health status of equipment and deterioration characteristics of fault. A time-response analysis function was used to predict the deterioration and fault accurately. A two-stage algorithm was proposed to divide the maintenance. An optimum maintenance strategy using combinatorial optimization of time periods to transform complex continuous time optimization problems was developed.[6] PdM scheduling model for various equipment is possible using the same methodology. ML model can be developed by considering the constraints of operating relationship on maintenance activities scheduling.

ML model can solve maintenance problems of multiple power equipment. David Kimera et al., 2020. applied PdM for ballast pumps in ship repair yards using Support Vector Machine (SVM) algorithm of unsupervised ML method where failure data was not available but historical operating data is available. For data acquisition various parameters such as flow rate, back pressure, amperage, suction pressure, and revolution per minute were considered. All these operating parameters were condition monitored for 40 weeks through data acquisition system to predict pump failure by SVM algorithm. An investigation on the behavior of the physical parameters on the tool was carried out. [13] A parallel prediction system like alarms should be set up in order to counter and compare the tool predictions during a flagging scenario. Other AI predictive algorithms could be developed.

Christoph Kammerer et al., 2021. used sensors for the data acquisition of thermal system. In this the

fan motor was operated at seven fixed speeds as 0%, 50%, 60%, 70%, 80%, 90% and 100% of the maximum engine speed. During operation of the fan motor, the sensors detected and recorded vibrations in the crankcase. In the multisensory study, the focus cluster algorithm combined with smoothed and differenced data produced the best results. The multi-sensor GY 521 gave the best results using the focus cluster algorithm. Focus cluster algorithm and Gradient Boost method used for analysis gives differentiated data up to 99.89%.[7] In further work a prediction model can be developed for prediction of wear and RUL of thermal system under automation.

Hardik Gohel et al., 2020 used logistic regression and support vector machines (SVM) algorithm of ML techniques to design and develop a predictive maintenance (PdM) framework for nuclear infrastructure. Based on data from an engine degradation simulation, the framework could forecast the infrastructure failure of nuclear power plants and also categorize the number of cycles. It gave precise results without penalty. [8] Data acquisition for real time data and modified ML algorithm can be used for PdM of nuclear plant.

A data analysis based predictive maintenance system was developed by Ayvaz Serkan et al.,2021 for mass and continuous flow production lines. Real time data acquisition was done by appropriate sensors, data analysis by ML algorithm was used to predict signals for future problems. Keras and Sci-kit learn ML libraries were used to develop ML model with Python programming for production line analysis. [9] The work addressed only frequently occurring fault, and hence a similar type of ML model can be implemented for rare faults and faults prediction by image processing.

Goran Putnik et al.,2021. developed semi-double-loop ML based intelligent Cyber-Physical System (CPS, or I-CPS) architecture. Data was collected and used in ML algorithm in three methods: 1) Combine data of all machines into single algorithm, 2) Combined data with separate machine ID in single algorithm 3) Separate data of each machine for respective individual algorithm. Twenty week's data was used in eight different algorithms as Random Forest, Support Vector Machine, Ensembled Learning, Naïve Bayes, Random Forest with 1 K learner, Random Forest with 100 K learning, and Decision Trees varying parameters, including hyperparameters tuning, in an automated cycle, through multiple iterations. F1 score of these 5 out of 8 algorithms was studied. [11] The work further can be extended up to investigation of new ML algorithm, learning "criticality index" which determines maintenance priority, between 0 and 1, development of a full, canonical I2-CPS.

Mustafa Cakir et. al., 2021. created IIoT based Industry 4.0 compatible with low-cost condition monitoring system. It executed in three steps: 1) Experimental setup and sensors for data acquisition, 2) IIoT based condition monitoring application and ML models, 3) Failure prediction done through

available data. During experimentation bearing data of induction motor through five different algorithms like Linear Discrimination Analysis (LDA), Support Vector Machine (SVM), Decision Tree (DT), k-nearest neighbor (kNN) and Random Forest (RF) was processed. Available data from condition monitoring could be evaluated based on factors like accuracy, precision, TNR, TPR, FPR, F1, FNR, score and, Kappa metrics. [12] Furthermore, deep learning algorithms can be used for real-time predictive maintenance, cost reduction and minimize energy consumption.

Panagou, S.,et.al. 2022. used 29 sensors to collect data from a rolling mill in a steel industry. XGBoost and a confusion matrix ML technique were used for further data analysis. The research work and investigation gave positive results to PdM using ML approach [14].

An intelligent predictive maintenance strategy using deep learning and augmented reality for machine tools in IoT-enabled manufacturing was presented by Changchun Liu et al.2022. An intelligent predictive maintenance approach to realize a highly reliable maintenance plan integrated with the fault prediction, accurate decision-making, and Augmented Reality (AR) was proposed. Convolutional Neural Network and Long Short-Term Memory (LSTM) methods were also used. The nonlinear relationship between the specified characteristics from the vast production data acquired by the IoT could be fitted by LSTM, and the specified features from the massive production data may be fully retrieved using CNN. [15] Further, the proposed methodology can be implemented for big manufacturing set up by using IoT technology. Prediction accuracy and efficiency of deep reinforcement algorithm can be improved by multi-agent reinforcement learning.

Roque A.S. et al.,2022 used Gradient Boosting and Random Forest algorithms of ML for predictive maintenance of rotating machine components. Accuracy up to 99.93% was achieved. [16] In future these algorithms can be applied and compared for other real-time datasets. Detailed analysis is possible on relationship between the models, data acquisition cost and hardware required. AI & ML technique could reduce the risk factor and maintenance cost. The advancement and growth made possible by these new technologies have made judgement processes simple and straightforward.

Studies conducted by Sircar A. et al, 2021 to access the intelligence of various ML techniques to proclaim its application for particular tasks in the oil and gas business. Artificial Neural Network (ANN), Linear regression, Fuzzy Logic etc. techniques were used for application of AI & ML in oil and gas industry. In future ML algorithms can be applied for fault diagnostics and prognostics in the oil and gas industry. [17].

Mohan, T. R., et. al. 2022. worked with the concept of conventional total productive maintenance used in Industry 3.0 setup, to develop intelligent ML based total productive maintenance solution to

achieve zero downtime in industrial machinery. It resulted in downtime reduction by 53% and breakdown occurrences were reduced by 54%. In high pressure sand moulding, the oil contamination level in machinery setup being a major breakdown parameter, the oil contamination value was determined by the sensor installed in the hydraulic unit and supplied into the local server through a wireless sensor network once every three minutes of interval in the minimum sampling period. ARIMA based total productive maintenance strategy to achieve zero downtime reaching as per Industry 4.0 standard was proposed. [20] In future, deep learning algorithm can be used in the condition monitoring of oil contamination and use of time series deep learning forecasting model to reduce breakdown time.

Bram Steurtewagen et al.2022, trained XGBoost model with combination of sensors to predict component failure in petrochemical machinery with the objective of failure prediction. Data was collected and implemented using a supervised ML approach, enriching the model with Shapley values for diagnostic insights [56].

Emiliano Traini, Giulia Bruno, et al., 2019. implemented milling cutting tool predictive maintenance strategy by collecting a real time milling data set. Decision Forest regression, Bayesian Linear Regression ML algorithm were used for validation of framework. [57].

Eleonora Florian et al. 2021 discussed the Receiver Operating Characteristics (ROC) curve-based mathematical model for a cost-based quantitative approach. The predictive maintenance implementation model is a helpful decision support system [58].

2.3 Literature review on challenges in Machine Learning Based Predictive Maintenance.

Application of ML algorithm for predictive maintenance strategies must be evaluated more precisely using performance metrics like cost reduction and maintenance task completion time. ML is a field that requires large amounts of data. Challenges related to data acquisition and big data need to be focus.

Dalzochio, J., Kunst, R., et al., 2021 discussed the challenges faced for implementation and use-case of PdM. Implementation of ML in PdM requires appropriate data acquisition system and huge database. In this work the challenges were divided into three groups: (I) Big Data analytics, (II) ML models, and (III) Ontology and reasoning-related proposals. A framework was created, and questionnaire was prepared to find out challenges in ML based PdM in the automobile industry, to ensure the functional safety rather than the product life cycle. [54] One of the reliable strategies to

overcome these challenges is predictive maintenance (PdM). A detailed evaluation is possible for parameters such as cost and time reduction. Practical approach can find out the challenges related to big data. Therefore parameters like latency, scalability and data security require further investigation.

Andreas Theissler et al., 2021. discussed about gaps in the implementation of ML strategy for predictive maintenance in automotive industry. The research work listed out few challenges as 1. Non-availability of real time database in public domain, 2. Lack of algorithm training data, 3. Complexity of problem solving, 4. Acceptance of prediction by ML algorithms, and 5. Complexity due to changes in the automotive industry [55].

Yan L et al.2022, presented a detail review of Non-Instructive Load Monitoring (NILM) methods of residential appliances and the challenges existing in each step of NILM. Important challenges were data acquisition, feature extraction, parameter learning and state interference. Hidden Markov Model and Deep Learning techniques were used for NILM methods. [56] There are many opportunities in the field of NILM and the broader application of NILM that should receive more attention.

Ferreira, C et al, 2022, identified fourteen challenges throughout the three macro-steps of the RUL prediction as:

a) **Data Extraction:** Time-varying sensor raw measurements are not significantly reflected by data extraction.

b) **Feature Extraction and Classification:** The complexity in the construction of health indicators is one of the challenges in feature extraction and classification. It deals with variety of operating conditions and deterioration patterns, Few other challenges are data noise, data sparsity, high level of uncertainty, censored data and variance of local features. Experts are required for Feature selection and its comparison, Training and testing data also significant challenge in this phase.

c) **Model Building and Training:** Few challenges in this are model uncertainty, Consider the chronological order and temporal correlation of the health monitoring data, Access to labeled failure data rare inaccuracy, Sensor data correlations are not explicitly considered in representation learning, Remaining Useful Life Prediction and Evaluation, Uncertainty Prediction, Single-path, and top-down propagation (DNN models), RUL Prediction Accuracy, Interpretability of the ML Results. Future scope for the work can segregate in four sections as find out new combinations and compare the results with reference. The second would be to modify existing methods by integrating knowledge-based

d) methodologies, The third would be to improve condition monitoring method and data driven model. some efforts required to generate more complex framework to predict RUL. [57].

Alanazi A et al. 2022, identified a crucial challenge in ML based prediction that it did not provide reasons and justification for the prediction except decision tree model. [58] More study is possible on use of AI ML algorithm to handle treatment of critical illness.

The main security risks and open challenges that IoT systems face were covered by Farooq U et al., 2022. IoT infrastructure produce huge data in mixed, uncertain format. Therefore, traditional ML techniques are not efficient in dealing with such situations and modifications. Few factors are very significant to tackle the above challenges are delay sensitive applications, device resources, data analytics etc. [59] In the future, more work is possible on intrusion and anomaly-based threats using deep learning method.

Zenisek, J et al.2019. presented a method to identify concept drift in data base as potential indication for defective system. Real time data of industrial radial fans through data acquisition system was collected, and reliable results gained from applying the detailed approach in this scope were discussed. ML tools as Linear regression, Random Forest, Symbolic regression algorithm for drift detection were used. According to the conducted data-based experiments and detailed analysis of experts on site at the stressed radial fan, concept drift detection was successfully deployed in the scope of the case study. However, the lack of continuous deterioration information made the predictability of concept drifts only based on an assumption difficult. [60] Further work will tackle this open issue and provide more detailed analysis for drift detection.

2.4 CASE STUDY: Condition Monitoring of a Dynamic System AI & ML

Introduction: The PdM tools are increasingly dependent on AI & ML based technology.

Naïve Bayes Algorithm: Naïve Bayes classifier works on probabilistic approach and is a common method for classification ML based AI technology.

The study is divided into three stages that are –

i. Fabrication of the testing setup
ii. Sensor interfacing
iii. AI coding and its training.

Fig.15. Testing setup design [46]

Table 3. Components used for project setup

Sr No.	Components	Sr No.	Components
1	Vibration Sensor	6.	MS Base Plate
2.	Motor	7.	Shaft
3.	USB to RS485 Convertor	8.	Channel
4.	Bearings	9.	Ethernet Shield
5.	Pulley	10.	Rubber Pad

Naïve Bayes classifier

Naïve Bayes classifier works on probabilistic approach and is a common method for classification. Multinomial Naive Bayes algorithm used as multiple variants with different frequencies and amplitude combinations, are used.

It estimates the conditional probability of a particular instance given in a class as the relative frequency of term belonging to class.

The variation considers the number of occurrences of term in training from class, including the multiple occurrences.

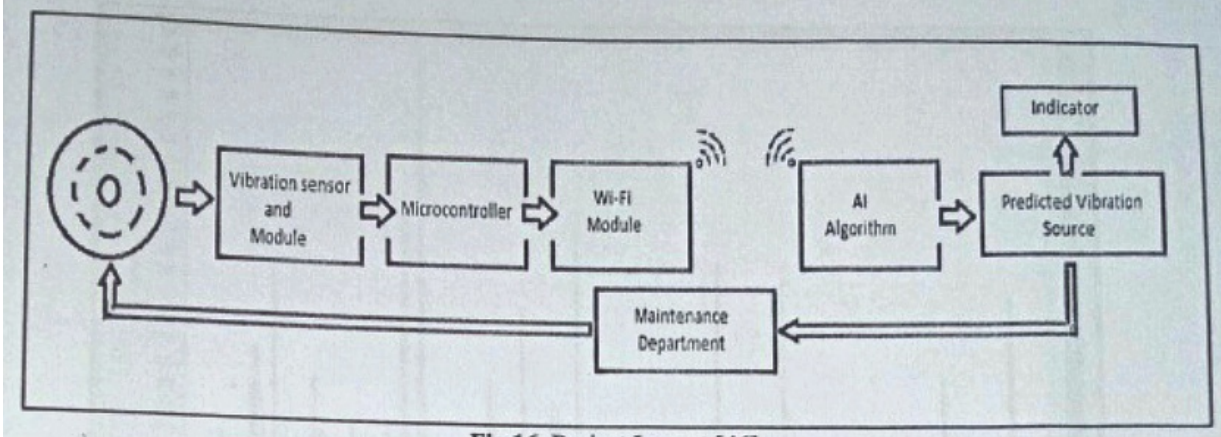

Fig.16. Project Layout [46]

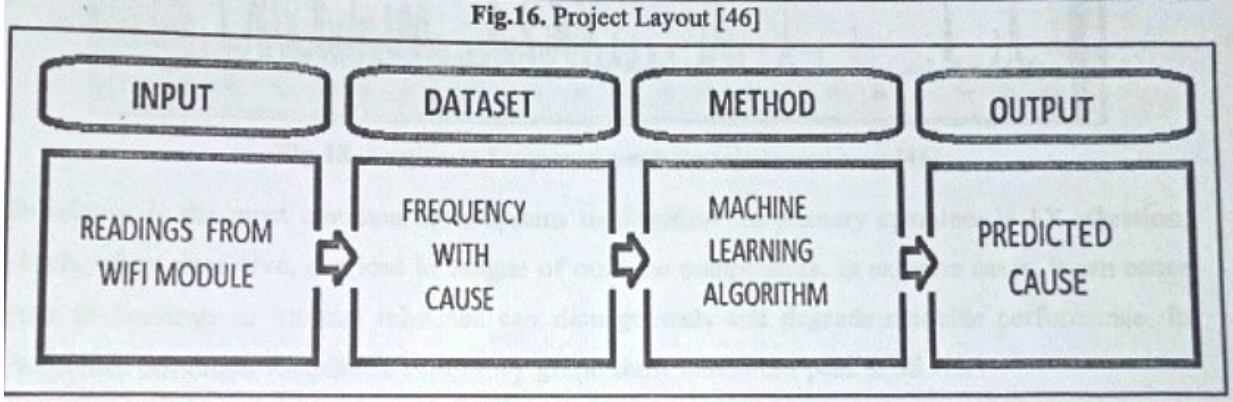

Fig.17. Block Diagram [46]

Working:

Tri-axial accelerometer is used to sense the vibrations. Vibrations that are sensed by the sensor are passed to the microcontroller (MSP 430) using sensor module.

The data received by microcontroller is then passed to Wi-Fi module which is further wirelessly transmitted to AI algorithm. Naïve Bayes algorithm contains CSV file in which ideal values of different vibration sources (bearing failure, shaft misalignment and mass unbalance) are stored in the form of data set.

Excessive vibrations are purposely added in the machine while it is in operating state.

The data that is received by AI algorithm is compared with the ideal data set and the source of vibration is predicted. The vibration source that is predicted by the AI algorithm is displayed on GUI.

Based on the analysis the maintenance action can be planned. The performance of the algorithm should be evaluated on the test data available from an authentic source.

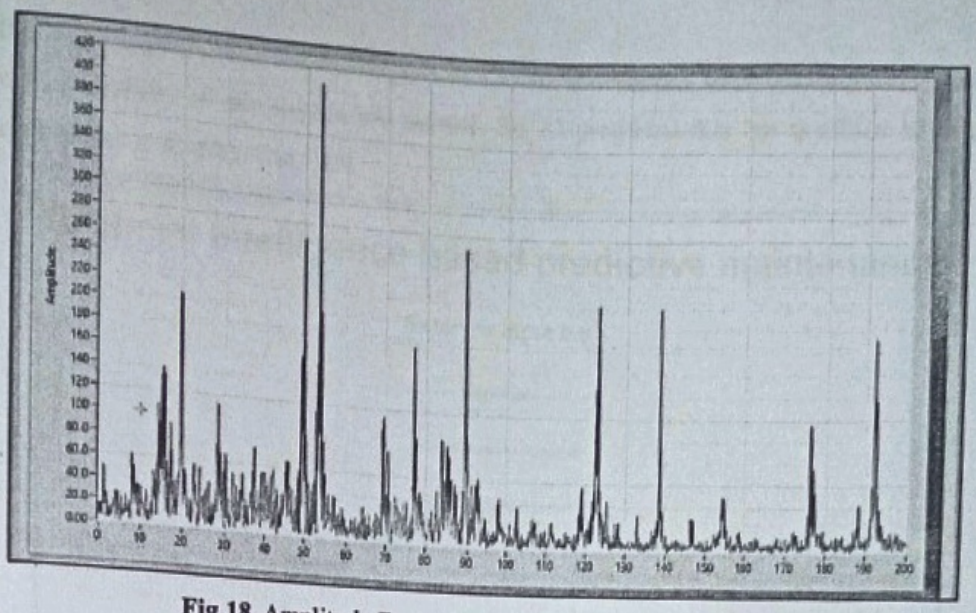

Fig.18. Amplitude-Frequency graph for unbalanced mass [46]

Unbalance is the most common rotor system malfunction. Its primary symptom is 1X vibration, which, when excessive, can lead to fatigue of machine components. In extreme cases, it can cause wear in bearings or internal rubs that can damage seals and degrade machine performance. In Unbalance condition Amplitude-Frequency graph show maximum peak at 55 Hz.

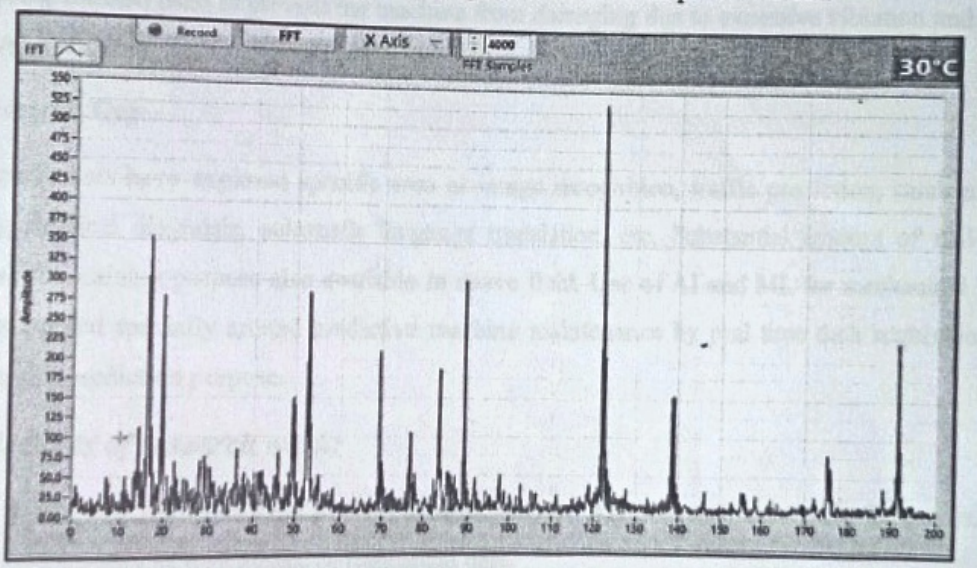

Fig.19. Amplitude-Frequency graph for Misalignment of shaft [46]

Coupling misalignment is a condition where the shaft of the driver machine and the driven machine are not on the same centerline. The non-coaxial condition can be parallel misalignment or angular misalignment as depicted. The more common condition is a combination of the two in both the horizontal and vertical direction. In above figure shows Amplitude-Frequency graph for parallel

Misalignment of shaft. Here maximum peak of 125 Hz is observed. Ideal situation were considered where all vibrations of the system are normal. So AI predicted that the condition is ideal. The predicted output is displayed in GUI.

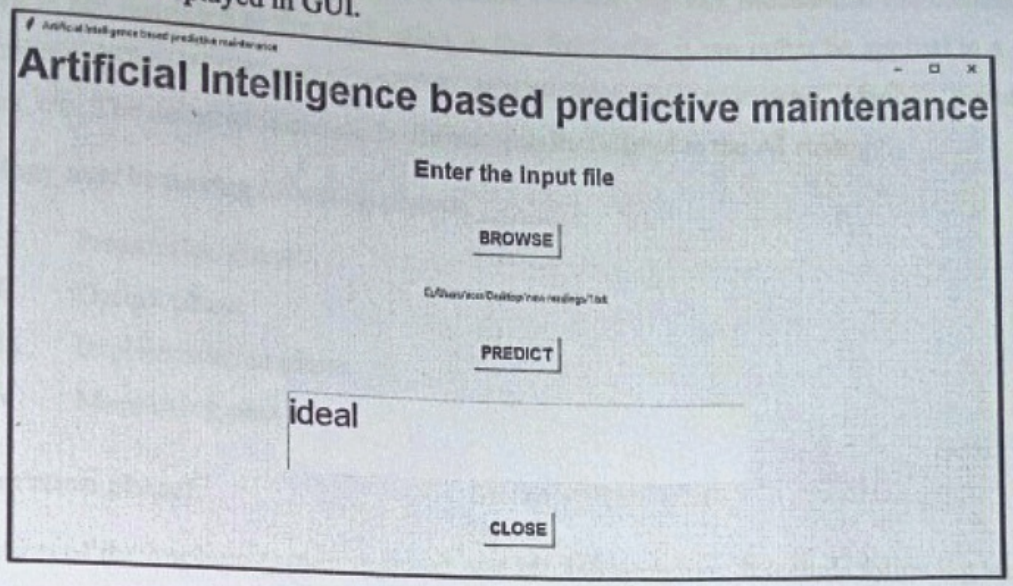

Fig.20. Graphic Design Interface [46]

In this cost-effective project the vibration sources of the rotating parts were predicted. Condition monitoring method used to prevent the machine from damaging due to excessive vibration and saves manpower and time, thus it provides additional value to the Maintenance department.

2.5 Research Gap

Few researchers have explored specific area as image recognition, traffic prediction, stock market trading, medical diagnosis, automatic language translation, etc. Substantial amount of real time database for training purpose also available in above field. Use of AI and ML for mechanical More work is needed specially around predictive machine maintenance by real time data acquisition for training and prediction purpose.

3. Objectives of research work:

1. To acquire real time data through sensors and use AI tools and techniques for analysis of sensory data as well available theoretical data.
2. To develop intelligent system for machine fault diagnosis.
3. To monitor machine health by condition monitoring.
4. To provide additional value to the maintenance department of medium and large-scale industries of various manufacturing domain by implementing PdM by Recent Advances of Industry 4.0

4. Methodology

Proposed work is to use AI & ML in Mechanical Engineering like Mechanical maintenance. The framework is not restricted to the application in this field only, it can rather be applied in a general way in many different use cases, such as quality impacting processes, advance procurement techniques, etc. The orientation should be fundamentally defined in the AI strategy.

Methodology may be having following phases.

I. Preparation phase.
II. Design phase
III. Implementation phase
IV. Monitoring phase

4.1 Preparation phase:

The selection of the implementation approach and ML infrastructure: It include following steps

A) Machine learning solution approach: The starting point is the problem identification and analysis to set objectives of research work, the important step is to define strategic goals for maintenance improvement that can only be reached with data mining and ML techniques economically. At the end clear and measurable goals have to be defined. Typically, possible machines and components either frequently fail unplanned and have high failure cost or are installed several times in the identical setup and thus offer a scaling effect. Then, it has to be checked if ML techniques are the most economical way to reach the defined

B) Maintenance ML use case: Once maintenance ML use case developed next step is to select suitable project approach.

C) ML Infrastructure: Depending on the selected project approach the type of ML infrastructure is influenced. It can be distinguished between the following basic types:

i. On premise solution with complete local IT hardware and software,
ii. Cloud based solution or Hybrid solution with varying part of local and cloud-based IT hardware and software.

4.2 Design phase:

The design phase follows mainly standard processes for completion of project, firstly the available data is to be sift and further data recording and processing is planned. Then the ML model is to be built

and evaluate. This takes up most of the time during the implementation of ML projects.

It consists of following steps

A) Checking data availability: Following the preparation phase, it must be checked which data is required for the design of the ML model. This includes

i. The definition of the first data set required in terms of measurands (AS-SHOULD-BE),
ii. Checking available data in terms of measurands, frequency, resolution and reliability (AS-IS),
iii. The comparison the two data sets and derivation which required data have to be collected additionally in terms of measurands, frequency, resolution and reliability and
iv. The derivation of required sensors and data collection systems.

Most important step here is the first assessment if these data are suitable in terms of consistency, frequency and resolution.

B) Data preparation:

Once the required data is collected and stored, it must be checked whether this data needs to be prepared, also known as data cleaning. This means that they are put into a form that can be used as a basis for data analysis, since the raw data are often not available in the correct format or have outliers. This is usually due to transmission or formatting errors that lead to incorrect, inconsistent, redundant or false data. Also, the test data set is split into training data and test data.

C) Selection and building of the maintenance ML model:

After preparing the test dataset, the appropriate ML algorithm has to be selected and then the model has to be built. ML algorithms can be distinguished in reinforcement learning, supervised, unsupervised and deep learning algorithms. Therefore, several algorithms and model parameters have to be tested in order to find the best matching algorithms.

D***) Evaluation of the model:*** After building the ML model, the evaluation step checks whether it meets the objective of the maintenance ML use case defined at the beginning. The ML model built is tested for its accuracy by applying to the unknown part of the test data set. Here the learned output is compared with the actual output. If the accuracy of the algorithm is not sufficient, model or data adjustments have to be made.

4.3 Implementation phase:

Once a stable and reliable ML model exists for the maintenance ML use case, it must be embedded in the factory environment and put into operation. On the one hand, the model is applied to live data to detect deteriorations in the condition or to predict failures in near real time.

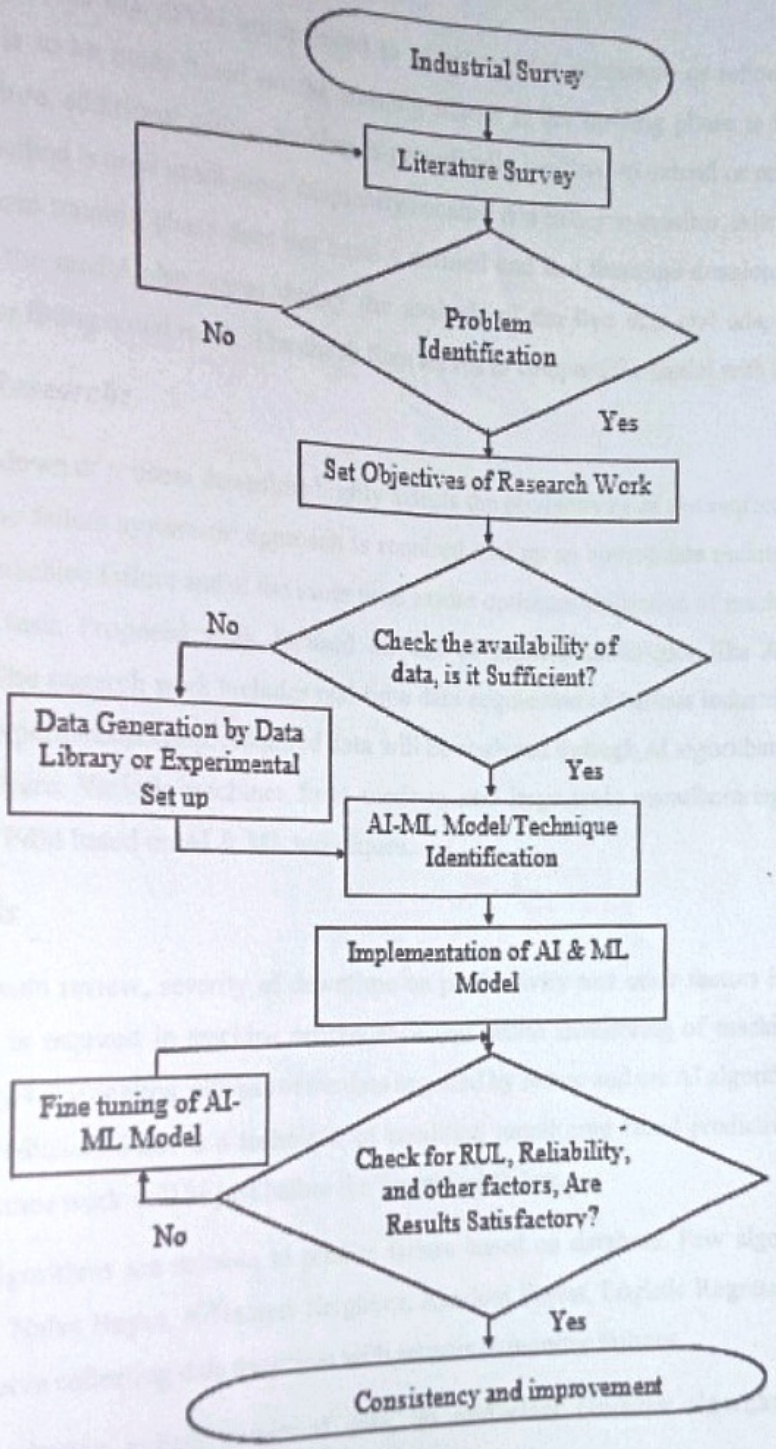

Fig.21. Flow Chart of Methodology

4.4 Monitoring phase:

Periodic checks of the ML model are required to adjust and for extensions or refinements. Here, a differentiation is to be made based on the training phase. If the training phase is limited in time Medicine structure, additional offline training is periodically required to extend or refine the model. This training method is used much more frequently because it is easier to monitor. Alternatively, there are models whose training phase does not have a defined end and therefore develops continuously. Consequently, the model also learns during the analysis of the live data and adapts accordingly, whereby an over fitting could result. The check then serves to compare the model with the defined KPI

5. Scope of Research:

Machine breakdown or process downtime highly affects the productivity of a manufacturing plant. To avoid a machine failure systematic approach is required. Set up an appropriate maintenance strategy which avoids machine failure and at the same time assure optimum utilization of machine parts life is a challenging task. Proposed work focused on use of modern techniques like AI for machine maintenance. The research work includes real time data acquisition of various industrial machines or its fabricated experimental setup. Acquired data will be analyzed through AI algorithms for prediction of machine failure. Various machines from medium and large-scale manufacturing units will be considered for PdM based on AI & ML techniques.

6. Hypothesis

Study of literature review, severity of downtime on productivity and other factors indicating more research work is required in machine maintenance and health monitoring of machine component. Further industry 4.0 is dealing with use of the data acquired by sensor and use AI algorithm for decision making and prediction. PdM is a technique of condition monitoring based predictive maintenance where maintenance work will be just before the functional failure.

Various ML algorithms are suitable to predict failure based on database. Few algorithms are like Decision Tree, Naïve Bayes, K-Nearest Neighbor, Random Forest, Logistic Regression etc. These techniques involve collecting data over time with sensors to monitor failures.

Condition monitoring collect numerical data, so multiclass classifier algorithm required for prediction. XGBoost, Random Forest are more suitable algorithm.

7. Summary:

Proposed research work is based on application of AI & ML for predictive machine maintenance. AI and ML base PdM can be done by two methods as condition monitoring and prognosis algorithm. Condition monitoring uses data from a machine to assess its current condition and to detect and diagnose faults in the machine using condition indicators. A condition monitoring algorithm derives metrics from the data called condition indicators. A condition indicator can be any quantity derived from the data that clusters similar system status together, thus a condition-monitoring algorithm can perform fault detection or diagnosis by comparing new data against the established markers of faulty conditions. Prognostics is forecasting when a failure will happen based on the current and past state of the machine. A prognostics algorithm typically use future value to estimates the machine's remaining useful life (RUL) or time-to-failure by analysing the current state of the machine.

Machine maintenance have an important role in productivity of manufacturing facilities. Equipment faults need to be identified and solved, avoiding shutdown in the production processes. ML methods have been emerged as a promising tool in PdM applications to prevent failures in equipment as well optimum utilization of remaining useful life. AI-based PdM can boost availability by up to 20%, Reducing inspection costs by 25%, Reducing annual maintenance cost by up to 10%, Asset productivity increases of up 20% is possible. PdM enhanced by AI allows for better prediction and avoidance of Machine failure by combining data from advanced Internet of Things (IoT) sensors and maintenance logs as well as external sources.

8. Future Work

1. End to End Implementation of AI & ML algorithm in Machine Maintenance.
2. Collaborate conventional machine maintenance strategies with recent technologies like IoT to contribute to Industry 4.0
3. Implementation of foolproof machine maintenance technique for Medium and large-scale, Continuous flow manufacturing plants.

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